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Research Proposal

Research Subject

"Design and Development of Effective Techniques for Detection of Covid-19 Cases"

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Abstract

COVID-19 is one the most infectious diseases in the world. The corona virus pandemic adversely affected the health of people around the world.

COVID-19 has already become a global health and economic threat and thousands of people have already died.

Deaths were initiated by respiratory failure, which leads to the failure of other organs too. Since many patients attend out-door or emergency, doctor's time is limited, and computer-aided diagnosis can save lives by early screening and proper-care. This will result in overall reduction of mortality rate.

Moreover, it is necessary to develop models capable of distinguishing Covid-19 cases from other similar viral cases, such as SARS, but also from a greater variety of common pneumonia or even physiological X-rays.

Computer-aided diagnostic tools can significantly improve the speed and accuracy of diagnosing cases with COVID-19. This could be highly useful in a pandemic, where the burden of disease and the need for preventive measures do not match the availability of resources.

In this research proposal we are planning to design and develop effective image processing technique which can be used to detect Covid-19 cases in the early stage. This will help the Doctors and professionals in a triage (decide the order of treatment of many patients) system to detect especially moderate and severe patients in panic situations.

Index

Abstract

1. Introduction 1

2. ReviewofLiterature 3

3. Objectives ofresearch 6

4. Methodologytobeadopted 7

5. Importance ofStudy 10

6. Proposed workplan 11

References 12

1. Introduction

Coronaviruses are a large family of different viruses. Some of them cause people to have colds. Others infect animals, including bats, camels, and cattle. The coronaviruses behind Middle East respiratory syndrome (MERS) and severe acute respiratory syndrome (SARS) developed from bats.

The virus first appeared on a small scale in November 2019 with the first large cluster appearing in Wuhan, China in December 2019. The virus is transmitted from one human to another on a large scale and spread whole across the Globe.

On March 11, 2020, the World Health Organization (WHO) declared coronavirus (COVID-19) as a pandemic due to its far-reaching seriousness throughout the world [2], [3]. Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus**.**

As of 18th March 2022, there have been 464,809,377 confirmed cases of COVID-19, including 6,062,536 deaths, reported to WHO [24]. Most people infected with this virus experienced mild to moderate respiratory illness and a few of them recovered without requiring special treatment. However, most of them became seriously ill and required medical attention. To fight the spread of COVID-19, early detection and immediate medical response to infected patients is a desperate necessity.

COVID-19 assaults the epithelial cells that line our respiratory tract which causes threat to life of patient in a week.

In clinical symptoms investigation it was found that Severe COVID-19 infections exhibit similar clinical characteristics to bronchopneumonia, such as fever, cough, and dyspnea [8]–[11].

Covid-19 cases are detected by the doctors or professionals by following techniques

- The CDC (Centers for Disease Control and Prevention) recommends a COVID-19 test called a nasopharyngeal swab for coronavirus.
- A real-time Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) test is currently used to detect COVID-19 cases. However, the test faces a critical problem of detecting false negatives and false positives, achieving sensitivity as low as nearly 60-70% [5]–[7].This procedure is the most widely used strategy for COVID-19 screening, but it is manual, confusing, relentless and a time-consuming process.

The test of COVID-19 was a difficult task due to the inaccessibility of the diagnosis system i.e COVID-19 testing kits and scarcity of doctors, professionals as compared with the huge number of patients everywhere, which was causing panic.

To identify depth and severity of the disease, X-rays are used to investigate the strength of a patient's lungs. The medical practitioner frequently uses X-ray images to analyze pneumonia, lung inflammation, abscesses, and enlarged lymph nodes. And almost all hospitals have X-ray imaging machines, it could be possible to use X Rays to test for COVID-19 without the dedicated test kits. However, X-ray examination needs a radiology master and takes a huge time, which is valuable when people are sick around the world. Therefore, developing an effective strategy is essential to save the life of patients and medical professional’s valuable time.

2. Review of Literature and development in the subject.

Several DL (Deep Learning) architectures using convolutional neural network namely, COVID-Net [12], DarkNet [13], CovidX-net [14], CheXnet [15], COVID-SDnet [16] and pre-trained CNNs [3], [17], [18]–[20] have been implemented to detect COVID-19 from viral pneumonia and normal chest radiographs. Few of the methods are briefed and a related summary is given in Table 1

(a) M. E. Chowdhury et al [3], has used a deep CNN based transfer learning approach for automatic detection of COVID-19 pneumonia. Posterior-to-anterior (AP)/anterior-to-posterior (PA) images of chest X-ray were used in this work as this view of radiography is widely used by radiologists in clinical diagnosis. Six different sub-databases were used to create one database.

(b) It was observed that DenseNet201 outperforms other different deep CNN networks while image augmentation was used for training the CNN models.

(c) CheXNet, is a variant of DenseNet, outperforms other networks while image augmentation was not used. The reason is theCheXNet was pre-trained on a large X-ray database, and it is showing better performance on this study while trained on a small non-augmented image dataset.

(d) In this work, authors have reported the findings from a large database along with the image augmentation to train shallow and deep networks and it was observed that deep networks perform better than the shallow networks particularly in classifying normal and viral images as most of the networks can identify COVID-19 with very high sensitivity.

(e) S. Asif and Y. Wenhui [17] has proposed a deep transfer learning-based approach. This uses chest X-ray images obtained from COVID-19 patients, normal and viral pneumonia for automatic detection of COVID-19 pneumonia. DCNN typically performs better with a larger dataset than a smaller one. Transfer learning can be beneficial in those applications of CNN where the dataset is not large. The idea of transfer learning using the trained model from large datasets such as ImageNet [21] is used for application with comparatively smaller datasets. This eliminates the requirement of having a large dataset and reduces the long training period as is required by the deep learning algorithm when developed from scratch.

(f) A. Narin, C. Kaya, and Z. Pamuk [18] have proposed an automatic prediction of COVID-19 using a deep convolution neural network based on pre-trained

transfer models and chest X-ray images. Performance results show that the ResNet50 pre-trained model yielded the highest accuracy.

(g) T. Ozturk et. al [13] have proposed a model that has 17 convolution layers. Covid-19 X-ray image database [29] is used in this work constantly updated with images shared by researchers from different regions. The Authors have proposed a deep learning-based model to detect and classify COVID-19 cases from X-ray images. The model is fully automated with an end-to-end structure without the need for manual feature extraction.

(h) P. R. Bassi and R. Attux [15] have suggested a technique of fine-tuned neural networks pre trained on ImageNet and applied a twice transfer learning approach, using NIH ChestX-ray14 dataset as an intermediate step. Author also suggested a novelty called output neuron keeping, which changes the twice transfer learning technique. To clarify the modus operandi of the models, Layer-wise Relevance Propagation (LRP) to generate heatmaps.

(i) S. Tabik et al. [22] have proposed COVID-SDNet methodology. that combines segmentation, data-augmentation, and data transformation. The obtained results show the high generalization capacity of COVID-SDNet, especially on severe and moderate levels as they include important visual features. The existence of few or nonvisual features in Mild and Normal-PCR+ reduces the opportunities for improvement. Introduced a dataset, named COVIDGR-1.0, with high clinical value. COVIDGR-1.0 includes the four main COVID severity levels identified by a recent radiological study and proposed a methodology, called COVID-SDNet,

(j) Jianpeng An et. al [34], have focused on screening COVID-19 in CXR images based on lung region as prior knowledge. The Author built MS-AdaNet, which utilizes multi-scale features in semantic prediction space to boost cross-domain lung segmentation tasks. Then further investigated the differences in lung regions in different pneumonia including COVID-19. Further, the multi-appearance CXR images were generated from MS-AdaNet for classification. MA-Net aggregated across the three appearances performed substantially better than any of the appearances on their own. Author validated MS-AdaNet for CXR domain adaptation on three public challenging lung segmentation datasets and achieved satisfactory results in different combinations of source and target domains.

(k) Qingsong Yao [41] has proposed the NormNet, a voxel-level anomaly modeling

network to recognize normal voxels from possible anomalies. A decision boundary for normal contexts of the NormNet was learned by separating healthy tissues from the diverse synthetic ‘lesions’, which can be further used to segment COVID-19 lesions, without training on any labeled data. The experiments on three different COVID-19 datasets validated the effectiveness of the NormNet. Author integrated multiple CT lung datasets for three different tasks of healthy lung modeling, COVID-19 lesion segmentation, and general-purpose lung segmentation into one working solution.

(l) CT Datasets for Healthy Lung Modeling: LUNA16 [42] is a grand-challenge on lung nodule analysis. The images are collected from The Lung Image Database Consortium image collection (LIDC-IDRI) [43], [44], [46], and each image is labeled by 4 experienced radiologists. As half of the images are healthy and clean except for those containing nodule areas, Author selected 453 CT volumes from LUNA16 and removed the slices with nodules to formulate the healthy lung CT dataset.

(m) CT Datasets for COVID-19 Lesion Segmentation: To measure the performance of the methods towards COVID-19 segmentation, Author chosen two public COVID-19 CT segmentation datasets and one UESTC with semantic labels. This method segments the COVID-19 lesions under the unsupervised setting, and thus the labeled datasets are only used for testing.

(n) CT Datasets for General Purpose Lung Segmentation: To obtain the accurate lung area in the CT volume, Author chosen nnU-Net [47] as the lung segmentation method and used three lung CT datasets with semantic labels for the lung region.

Author	Dataset	Method	Classification scheme	Evaluation Results
Linda Wang et al. [24]	COVIDX dataset: 16756 chest x-ray images from open repositories	COVID-Net	Normal vs Non-COVID vs COVID -19	Accuracy=93.3%
Hafeez Abdul et al. [30]		Pre-trained ResNet50 model		Accuracy=90%
Ozturk et al. [25]	142 COVID-19, 500 normal, and 500 viral pneumonia images	DarkNet Model	COVID-19 vs non-finding	Accuracy = 98.08%
			COVID-19 vs non-finding vs viral pneumonia	Accuracy= 87.02%
Hemdan et al. [27]	25 Normal and COVID-19 images	CovidX-Net	Normal vs COVID-19	Accuracy=90% F1-score = 0.89 and 0.91 for normal and COVID-19 respectively using DenseNet201
Narin et al. [28]	50 COVID-19 images from GitHub dataset and 50 normal images from Kaggle dataset	Pre-trained ResNet50	Normal vs Viral Pneumonia vs COVID-19	Accuracy= 97% using Inception V3 model and 87% for Inception-ResNet V2 model
Ioannis et al. [29]	Dataste1: 224 COVID-19, 700 bacterial pneumonia, and 504 normal x-ray images, Dataste2: 224 COVID-19, 712 bacterial and viral pneumonia, and 504 normal x-ray images	Different fine-tuned DL models	Normal vs. COVID-19 vs. Viral Pneumonia	Accuracy=96.7%, Sensitivity=98.66%, Specificity=96.46%
Asif et al. [9]	864 COVID-19, 1341 normal, and 1345 viral pneumonia x-ray images	Pre-trained Inception V3 model	Normal vs. COVID-19 vs. Viral Pneumonia	Accuracy=96%
Chowdhury et al. [2]	**Kaggle Dataset: 219 COVID-19, 1341 Normal, and 1345 Viral Pneumonia**	**Pre-trained CNN models**	**Normal vs COVID-19**	**Accuracy= 98.3%**
			Normal vs COVID-19 vs. Viral Pneumonia	**Accuracy=98.3%**
Bassi et al. [27]		**CheXNet**	**Normal vs COVID-19 vs. Viral Pneumonia**	**Accuracy=97.8%**
Tabik et. al [52]	COVIDGR dataset: 852 images with 426 images non-COVID-19 and COVID-19	**COVID-SDnet**	**Non-COVID vs COVID**	**Accuracy=76.18±2.70**

Table 1: Literature Review for The Covid-19 Detection [1]

3. Objectives of research

Research objectives are framed as given below:

RO1. Literature review and to study available techniques for detection of Covid-19 cases.

RO2. To identify the limitations of existing techniques

RO3. To design and develop the technique to overcome the identified limitations.

RO4. To analyze the performance of proposed technique on standard database

RO5. To verify the proposed technique on a real database.

RO6. To compare the performance of proposed techniques in terms of its computational complexity.

4. Methodology to be adopted

Proposed methodology for detection of Covid-19:

(a) Preprocessing using Illumination invariant Image enhancement technique
(b) Feature Extraction Using
    i. Local Binary Pattern (LBP)
    ii. Fibonacci-p patterns
    iii. Shape Dependent Fibonacci Pattern.
(c) Covid-19 detection using
    i. Deep Convolution Neural Network
    ii. Deep Transfer Learning Approach
(d) Performance Evaluation using
    i. Computational Complexity
    ii. Accuracy
    iii. Recall
    iv. Specificity
    v. Precision

Local Binary Patterns (LBP): is a texture descriptor that utilizes the center pixel's information and its respective neighboring pixels to encode the structural and statistical texture information present in an image.

Fibonacci-p patterns: Fibonacci-p patterns are textural feature descriptors that work very similar to LBP, i.e., they also encode the textural pattern information surrounding every pixel present in an image by assigning appropriate Fibonacci weights to them. However, the difference between LBP and Fibonacci -p patterns is that in the latter, a set threshold value is used for binarizing the mxn neighborhood. If the difference between the center pixel and its respective neighboring pixels is greater than or equal to the set threshold value, the neighboring pixel is binarized as 'one,' or else is binarized as 'zero'. To generate the decimal value, Fibonacci weights are assigned to the obtained binary pattern and summed together**.**

Shape-dependent Fibonacci -p patterns: use the different shapes as per the structural pattern to encrypt the textural information present in an image. The main advantage of shape-dependent Fibonacci -p patternsis the encoding of the textural patterns aligned in different directionsand shapes in the image all in one operation.

Another advantage of Shape-dependent Fibonacci -p patterns isthat they can detect different textures and discontinuities suchas spots, flat areas, edges and edge ends, and curves.

Deep convolutional neural networks (DCNN) are the type most used to identify patterns in images and videos. DCNNs have evolved from traditional artificial neural networks, using a three-dimensional neural pattern inspired by the visual cortex of animals.

Deep convolutional neural networks are mainly focused on applications like object detection, image classification, recommendation systems, and are also sometimes used for natural language processing.

The strength of DCNNs is in their layering. A DCNN uses a three-dimensional neural network to process the red, green, and blue elements of the image at the same time. This considerably reduces the number of artificial neurons required to process an image, compared to traditional feed forward neural networks.

Deep convolutional neural networks receive images as an input and use them to train a classifier. The network employs a special mathematical operation called a“convolute-ion” instead of matrix multiplication.

Deep Transfer Learning Approach:

Transfer learning is the reuse of a pre-trained model on a new problem. It is popular in deep learning because it can train deep neural networks with comparatively little data. This is very useful in the data science field since most real-world problems typically do not have millions of labeled data points to train such complex models.

In transfer learning, the knowledge of an already trained machine learning model is applied to a different but related problem.

Transfer learning, try to exploit what has been learned in one task to improve generalization in another. It transfers the weights that a network has learned at "task A" to a new "task B." The general idea is to use the knowledge a model has learned from a task with a lot of available labelled training data in a new task that doesn't have much data.

Transfer learning has several benefits, but the main advantages of are saving training time, better performance of neural networks (in most cases), and not needing a lot of data.

With transfer learning a solid machine learning model can be built with comparatively little training data because the model is already pre-trained. Additionally, training time is

reduced because it can sometimes take days or even weeks to train a deep neural network from scratch on a complex task

The flow of detection of Covid-19 is represented in the fig.1 This includes Image acquisition, Image pre-processing, feature extraction, and the extracted features are used for detection, classification.

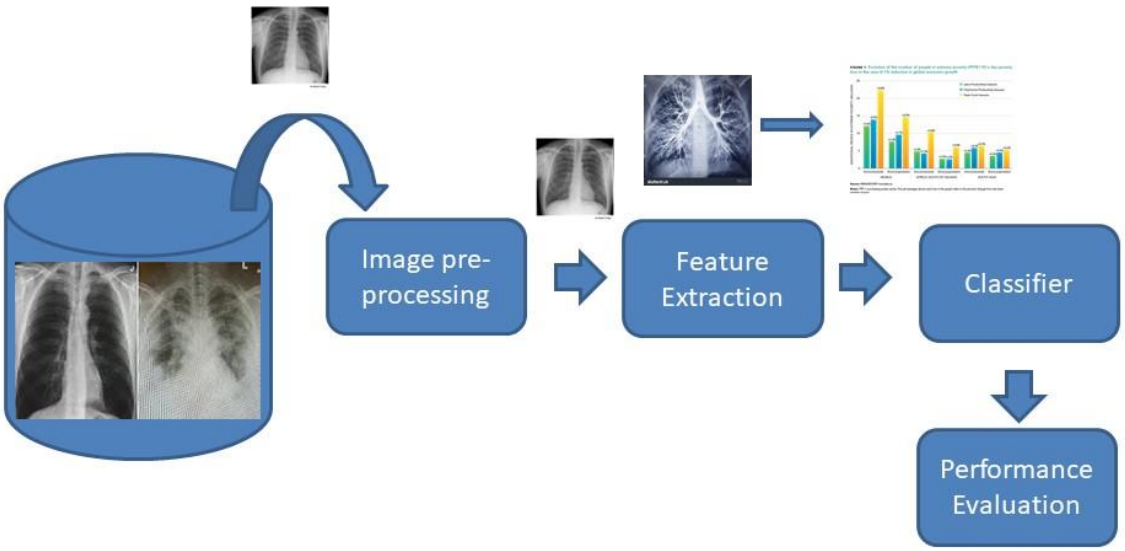

Fig. 1 Flowchart of Covid-19 Detection

Dataset to be Utilized:

(a) COVIDGR 1.0

Under a close collaboration with an expert radiologist team of the Hospital Universitario San Cecilio, the COVIDGR-1.0 dataset of patients' anonymized X-ray images has been built. 852 images have been collected following a strict labeling protocol. They are categorized into 426 positive cases and 426 negative cases. Positive images correspond to patients who have been tested positive for COVID-19 using RT-PCR within a time span of at most 24h between the X-ray image and the test. Every image has been taken using the same type of equipment and with the same format: only the posterior-anterior view is considered. More information about image distribution**:**

Class	#images	women	men
negative	426	239	187
positive	426	190	236

(b) Kaggle dataset:Chest X-Ray Images (Pneumonia)

5. Importance of Study

In case of disasters such as COVID-19 pandemic, demanding health services at the same time, collapse of the health system is inevitable due to the insufficient number of hospital beds and health personnel.

Also, COVID-19 is a highly contagious disease, and doctors, nurses, and supporting staff of hospitals are most at risk. Early diagnosis of pneumonia has a vital importance both in terms of slowing the speed of the spread of the epidemic by quarantining the patient and in the recovery process of the patient [13].

13.01 lakh (1.301 million) doctors listed in the Indian Medical Registry, mentioned in the Lok Sabha in December 2021. Some of them are died, retired, stopped practice, or migrated.

10.41 lakh (arbitrary number 80%) doctors currently practicing in India, which is a

doctor : patient (D:P) ratio of 0.74:1000, for a population of 1.40 billion (140 crores) as of December 2021. The WHO recommendation is a minimum D:P ratio of 1:1000. [48] Looking at the constraints of the resources and professionals Computer-aided diagnostic tools can significantly improve the speed and accuracy of diagnosing cases with COVID-19. This is the need of society.

6. Proposed work plan:

Sr No	Year	Research Activity	Research Objectives	Target to be achieved
1	2021-22	Literature review, to study available techniques for detection of Covid-19 and identify the limitations	RO1, RO2	Journal Paper I/ Conference Paper I
2	2022-23	Design and develop the technique to overcome the limitations and to analyse the performance on standard d0atabase	RO3, RO4	Conference Paper II, Journal Paper II
3	2023-24	Verify the proposed technique on a real database and compare the performance in terms of its computational complexity. Pre Ph.D.-Synopsis Submission, Thesis writing, Thesis Submission	RO5, RO6	Conference Paper III / Book Chapter I

Table2: Year-wisework-plan

References

[1] Karen Panetta, ForamSanghavi, SosAgaian, Neel Madan, "Automated Detection of COVID-19 Cases on Radiographs using Shape-Dependent Fibonacci-p Patterns", IEEE Journal OF Biomedical and Health Informatics, VOL. 25, NO. 6, JUNE 2021. doi: 10.1109/JBHI.2021.3069798. Epub 2021 Jun 3.

[2] "WHO director-general's opening remarks at the media briefing on COVID-19 - March 11, 2020," accessed Jun. 2, 2020. [Online]. Available: https://www.who.int/dg/speeches/ detail/who-directorgeneral-s-opening-remarks-at-the-media-briefing-on-covid-19

[3] M. E. Chowdhury et al., "Can AI help in screening viral and COVID-19 pneumonia?" 2020, arXiv:2003.13145.

[4] "WHO coronavirus (Covid-19) situation reports-189," accessed Jul. 28, 2020. [Online]. Available:https://www.who.int/docs/defaultsource/coronaviruse/situation-reports/2020072 7-covid-19 -sitrep-189.pdf?sfvrsn=b93a6913_2

[5] J. P. Kanne, B. P. Little, J. H. Chung, B. M. Elicker, and L. H. Ketai, "Essentials for radiologists on COVID-19: An update—Radiology scientific expert panel," ed: Radiological Society of North America, 2020.

[6] T. Ai et al., "Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases," Radiology, vol. 296, no. 2, pp. E32–E40, 2020.

[7] Y. Fang et al., "Sensitivity of chest CT for COVID-19: Comparison to RT-PCR," Radiology , vol. 296, no. 2, pp. E115–E117, 2020.

[8] D. Wang et al., "Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China," Jama, vol. 323, no. 11, pp. 1061–1069, 2020.

[9] N. Chen et al., "Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in wuhan, china: A descriptive study," Lancet, vol. 395, no. 10223, pp. 507–513, 2020.

[10] C. Huang et al., "Clinical features of patients infected with 2019 novel coronavirus in wuhan, china," Lancet, vol. 395, no. 10223, pp. 497–506, 2020.

[11] Q. Li et al., "Early transmission dynamics in wuhan, china, of novel coronavirus–infected pneumonia," New England J. Med., 2020.

[12] L.WangandA.Wong, “COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images,” 2020, arXiv: 2003.09871, .

[13] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. Rajendra Acharya, “Automated detection of COVID-19 cases using deep neural networks with X-ray images,” Comput. Biol. Med., 2020, Art. no. 103792, doi: 10.1016/j.compbiomed.2020.103792.

[14] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, “Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in X-ray images,” 2020, arXiv:2003.11055.

[15] P. R. Bassi and R. Attux, “A deep convolutional neural network for COVID-19 detection using chest X-Rays,” 2020, arXiv:2005.01578.

[16] S. Tabik et al., “COVIDGR dataset and COVID-SDNet methodology for predicting COVID-19 based on chest X-Ray images,” IEEE J. Biomed. Health Inform., vol. 24, no. 12, pp. 3595–3605, Dec. 2020.

[17] S. Asif and Y. Wenhui, “Automatic detection of COVID-19 using X-ray images with deep convolutional neural networks and machine learning,” medRxiv, 2020.

[18] A. Narin, C. Kaya, and Z. Pamuk, “Automatic detection of coronavirus disease (covid-19) using X-ray images and deep convolutional neural networks,” 2020, arXiv:2003.10849.

[19] I. D. Apostolopoulos and T.A.Mpesiana, “Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks,” Phys. Eng. Sci. Med., p. 1, 2020.

[20] M. Farooq and A. Hafeez, “Covid-resnet: A deep learning framework for screening of covid19 from radiographs,” 2020, arXiv:2003.14395.

[21] Google Cloud Platform, Image classification Transfer learning with Inception V3. Available online:https://codelabs.developers.google.com/codelabs/cpb102-txflearning/index.html. Accessed December 20, (2017).

[22] S. Tabik et al., “COVIDGR dataset and COVID-SDNet methodology for predicting COVID-19 based on chest X-Ray images,” IEEE J. Biomed. Health Inform., vol. 24, no. 12, pp. 3595–3605, Dec. 2020.

[23] https://tr.euronews.com Accessed 4 October 2020.

[24] https://covid19.who.int/

[25] S.-I. S. o. M. a. I. Radiology. (2020). COVID-19 Database. Available:https://www.sirm.org/category/senza-categoria/covid-19/

[26] Cohen JP, Morrison P, and Dao L. COVID-19 Image Data Collection. arXiv:2003.11597, 2020.

[27] Wang X, Peng Y, Lu L, Lu Z, Bagheri M, and Summers RM. ChestX-Ray8: Hospital- Scale Chest X-Ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, pp. 3462-3471,https://doi.org/10.1109/CVPR.2017.369, 2017.

[28] Mooney P. Chest X-ray Images (Pneumonia). Kaggle Repository: https://www.kaggle.com/paultimothymooney/chest-xray-pnemonia, 2018.

[29] J.P. Cohen, COVID-19 Image Data Collection, 2020.https://github.com/ieee8023/COVID-chestxray-dataset.

[30] P. C. Joseph, M. Paul, and D. Lan, COVID-19 Database, 2020. [Online]. Avaliable: https://github.com/ieee8023/covid-chestxray-dataset

[31] L.Wang et al., "COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images," 2020.

[32] Chung et al., "Figure 1 COVID-19 chest X-ray dataset initiative," 2020. [Online]. Available:https://github.com/agchung/Figure1-COVID-chestxray-dataset

[33] "Radiological Society of North America. RSNA pneumonia detection challenge," 2019. [Online]. Available:https://www.kaggle.com/c/rsnapneumonia-detection-challenge/data

[34] Jianpeng An, Qing Cai ,Zhiyong Qu , and Zhongke Gao," COVID-19 Screening in Chest X-Ray Images Using Lung Region Priors",IEEE Journal of Biomedical and Health Informatics, vol. 25, NO. 11, November 2021.

[35] J. Shiraishi et al., "Development of a digital image database for chest radiographs with and without a lung nodule: Receiver operating characteristic analysis of radiologists' detection of pulmonary nodules," Amer. J. Roentgenol., vol. 174, no. 1, pp. 71–74, 2000.

[36] B. Van Ginneken, M. B. Stegmann, and M. Loog, "Segmentation of anatomical structures in chest radiographs using supervised methods: A comparative study on a public database," Med. Image Anal., vol. 10, no. 1, pp. 19–40, 2006.

[37] S. Stirenko et al., "Chest X-ray analysis of tuberculosis by deep learning with segmentation and augmentation," in Proc. IEEE 38th Int. Conf. Electron. Nanotechnol., 2018, pp. 422–428.

[38] S. Jaeger et al., "Automatic tuberculosis screening using chest radiographs," IEEE Trans. Med. Imag., vol. 33, no. 2, pp. 233–245, Feb. 2014.

[39] S. I. S. o. M. a. I. Radiology, COVID-19 Database, 2020. [Online]. Avaliable:https://www.sirm.org/category/senza-categoria/covid-19/

[40] P. Mooney, Chest X-Ray Images (Pneumonia), 2018. [Online]. Available:https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[41] Qingsong Yao, Li Xiao, Member, PeihangLiu ,S. Kevin Zhou , "Label-Free Segmentation of COVID-19 Lesions in Lung CT", IEEE Transaction on Medical Imaging,vol. 40, no. 10, October 2021.

[42] LUNA16. Accessed: 2020. [Online]. Available: https://luna16.grand-challenge.org/Home/

[43] S. G. Armato et al., "Data from LIDC-IDRI," in The Cancer Imaging Archive. 2015, doi: 10.7937/K9/TCIA. 2015.LO9QL9SX.

[44] S. G. Armato et al., "The lung image database consortium (LIDC) and image database resource initiative (IDRI): A completed reference database of lung nodules on CT scans," Med. Phys., vol. 38, no. 2, pp. 915–931, Jan. 2011, doi: 10.1118/1.3528204.

[45] UESTC-COVID-19. Accessed: 2020. [Online]. Available:http://faculty. uestc.edu.cn/HiLab/en/article/379152/content/3319.htm

[46] K. Clark et al., "The cancer imaging archive (TCIA): Maintaining and operating a public information repository," J. Digit. Imag., vol. 26, no. 6, pp. 1045–1057, Dec. 2013.

[47] F. Isensee, P. F. Jäger, S. A. A. Kohl, J. Petersen, and K. H. Maier- Hein, "Automated design of deep learning methods for biomedical image segmentation," 2019, arXiv:1904.08128. [Online]. Available: http://arxiv.org/abs/1904.08128

[48] https://timesofindia.indiatimes.com/blogs/voices/we-dont-even-know-how-many-doctors-currently-practice-in-india/

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